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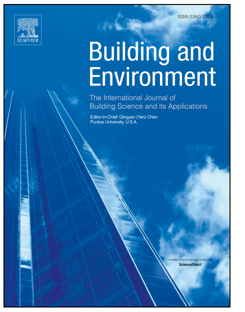

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Probabilistic adaptive thermal comfort for resilient design

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Abstract

Adaptive thermal comfort theory has become the bedrock of much thinking about how to judge if a free-running environment is suitable for human occupation. In design work, the conditions predicted by a thermal model, when the model is presented with one possible annual weather time series (a reference year), are compared to the limits of human comfort. If the temperatures are within the comfort limits, the building is judged to be suitable. However, the weather in many locations can vary year-on-year by a considerable margin, and this begs the question, how robust are the predictions of adaptive comfort theory likely to be over the many years a building might be in use? We answer this question using weather data recorded for up to 30 years for locations within each of the five major Köppen climate classifications. We find that the variation in the annual time series is so great that the predicted comfort temperature frequently lies outside the acceptable range given by the reference year. Return periods for the excursions of the time series are calculated for each location. The results for one location are then validated using the world's longest temperature record. These results suggest that industry and academia would be best advised to move to a probabilistic methodology, like the proposed one, when using adaptive comfort theory to judge the likely conditions within a building. Extra pertinence is provided by concerns over increases in mortality and morbidity in buildings due to a rapidly warming climate.

Keywords: adaptive thermal comfort, robust building design, Test Reference Year, Design Summer Year

Highlights

- The variability of historical weather time series studied for locations within each of the five major Köppen climate classifications.
- A new probabilistic adaptive comfort theory introduced.
- New comfort equations for resilient building design presented.

1. Introduction

There has been a growing realisation that the use of a single air temperature to represent the preferred temperature of a group of occupants is invalid in the case of free-running buildings where occupants have the ability to adjust their environment, for example by altering clothing levels and opening windows. In such cases the preferred temperature is better represented by the adaptive thermal comfort theory. This accounts for the adaptation of the individuals to the external temperature during the previous days. As this results in preferred temperatures rising during the summer, and falling in winter, the approach can also lead to lower conditioning energy use [1, 2], and hence is a common strategy in low-energy design. The approach has been given extra weight by its adoption in building codes and regulations via the ANSI-ASHRAE Standard 55 [3] and the European EN-15251 [4].

To apply the approach during the design phase, a thermal simulation of the building is completed and the predicted temperatures are compared to those given by the adaptive thermal comfort theory (which generates a range of acceptable temperatures). If the temperatures inside the building are within this range, it is assumed that the occupants will in general be satisfied and no conditioning will be needed. This simulation requires a weather file for the location in question and, as in most design work, a single representative year of weather (observed or artificially created) is used. This begs the question, how different might the answer be if a different year of weather was used? I.e. when applied within a design setting, rather than a research one, how robust is the adaptive thermal comfort method. As the adaptive thermal comfort approach is used for simulating buildings without air conditioning, an error here can lead to fatal consequences. In the 2003 European heatwave 14,000 people died in Paris alone - almost all in free-running buildings [5]. As the predictions of climate change are for a much warmer world [6], with longer, more intense and more frequent heatwaves [7-9], there is a growing risk of heat-related morbidity and mortality [10-12] and a need to ensure resilient buildings.

Adaptive thermal comfort makes use of a running mean outdoor air temperature taken over the previous days. Hence there has been a tacit assumption that the smoothing of the weather data that this implies leads to a representative year giving acceptable temperatures that are very close to those that would occur in any real year.

In this paper we examine whether this is really so. This is achieved by using approximately thirty years of weather data recorded at five locations, one in each of the major climatic regions of the world according to the Köppen classification [13], and three additional locations in the UK, plus 3,000 years of synthetic data generated for the three UK locations. From this data, the range of acceptable temperatures is calculated and a series of statistical methods is applied to study how the data spans in both temperature and temporal space. This ultimately results in a new probabilistic adaptive thermal comfort model which can be directly used for the resilient design, via thermal simulation, of free-running buildings. The return periods of this model are validated for London against the Central England

Temperature Record, which spans 358 years, from 1659 to today; then the predictions are themselves validated by comparing the excursions predicted by the model and those given by the weather generator.

1.1. Representative weather

Building simulation is normally based on the use of representative weather time series. These representative weather files summarise weather conditions for a location. This includes hourly data on temperature, dew point, direct and diffuse solar radiation, wind speed and wind direction, etc. These files are used to estimate the average building energy use and carbon emissions [14, 15]. A typical representative weather file is created from historical data (usually around 20-30 years of data, depending on data availability), and compiled by comparing the cumulative and empirical distribution functions of different meteorological variables within the base dataset.

The Test Reference Year (TRY), for example, is composed of 12 separate months of data each one chosen to be the most average month among a set of base years [16]. The cumulative distribution functions on which the TRY is based are made up of the daily mean values of three parameters: dry bulb temperature, cloud cover (used as a proxy for solar irradiation), and wind speed. These daily means are computed using hourly values from all the months of the base years considered. Component months are chosen using the Finkelstein-Schafer (FS) statistic method, essentially, those months with the most average values of temperature, radiation and wind speed combined. In the case of the TRY, each of the 3 environmental parameters carries an equal weighting; this was deemed an appropriate method for naturally ventilated buildings [16].

By contrast, the Design Summer Year (DSY) [16] is primarily an attempt to estimate the impact of warmer than average summers. It was initially intended for the sizing of mechanical cooling systems and is now used for assessing the risk of overheating in naturally ventilated buildings. The DSY is the year that falls in the middle of the upper-quartile of the base years' dataset, ranked according to summertime (April to September) average dry bulb temperature; this is generally the third warmest summer for a base dataset of 20 years. The DSY does not take into account extreme temperatures in individual months or incident solar radiation, both of which are of great significance for assessing the overheating performance of buildings [17]. This means that periods of high temperature (such as heat waves) in relatively cool summers are not considered. This is a problem, as summers such as 2003 which resulted in so many deaths across Europe are not ranked highly in the base dataset when considering average summertime temperature. Various attempts have been made to address such concerns, largely by creating new reference years based on warmer periods or on predictions of climate change (see, for example: [18-23]).

Although the DSY might be appropriate for measuring overheating duration it is unlikely to be suitable for looking at severity of overheating due to its simple selection method [24]. Weighted cooling degree hours have been suggested as an alternative metric for the selection of a DSY that might solve this [18, 25]. Furthermore, as it is known that different weather parameters have a differing influence on the relative risk of overheating for different building types [23], three design reference years were selected in [26] based on the daily mean temperature, relative humidity and solar radiation respectively. In addition, different sampling methods [26, 27] and statistical adjustment methods [28] have been used to develop new DSYs but none of them have been found to overcome all the shortcomings in the simple DSY selection discussed in [29].

Here we take a different approach by retaining the reference year and adding resilience by making the upper and lower bounds of the comfort equation probabilistic.

1.2. Adaptive thermal comfort

The adaptive thermal comfort theory was first introduced by Nicol and Humphreys in the 1970s [1]. An adaptive model was then incorporated into the ANSI/ASHRAE Standard 55 in 2004 thanks to the research of Brager and De dear [2] who assembled the ASHRAE RP-884 database from more than 21,000 thermal comfort measurements primarily in office buildings in Thailand, Indonesia, Singapore, Pakistan, Greece, UK, USA, Canada and Australia. The adaptive model of the ANSI/ASHRAE Standard 55 [3] and its European counterpart (EN 15251) [4] are driven by the idea that in free-running spaces there exists a wide band of temperatures within which an occupant can find his/her own optimum given sufficient adaptive opportunities.

According to the adaptive theory [2, 30], thermal comfort is not merely the result of a body's thermal balance but is the outcome of a continuous process of adaptation involving physiological, psychological and behavioural adaptation. The physiological responses of the human body to environmental stimuli have been widely studied in the literature [31-33]. Psychological adaptation includes any psychological reaction to sensory information, such as habituation, relaxation of thermal expectations and gradual change of preferences. Behavioural adaptation refers to all the conscious or unconscious actions that, when the environmental stimuli are perceived as discomforting, a person can take in order to modify the building indoor environment, their personal situation or both of these, such as taking on/off clothing, consuming hot/cold food and hot/cold drinks, opening/closing windows and doors, and drawing curtains. This is in agreement with the fundamental precept of the adaptive model: ‘if a change occurs such as to produce discomfort, people react in ways which tend to restore their comfort’ [2]. Of the three forms of adaptive opportunities, this is the one in which occupants have the opportunity to play an active role.

Both the ASHRAE and European adaptive comfort models consider the process of thermal adaptation as a black box and integrate occupant thermal expectations and adaptive actions in a single linear equation predicting indoor comfort temperatures from outdoor temperatures. Within the ASHRAE adaptive thermal comfort model [3], the upper and lower allowable indoor operative temperature limits (T_{upper} and T_{lower}) depend on the outdoor temperature T_{out} (Figure 1):

$$T_{upper} = (0.31 \cdot T_{out} + 17.8) + 3.5, \text{ and} \tag{1}$$

$$T_{lower} = (0.31 \cdot T_{out} + 17.8) - 3.5 \tag{2}$$

where T_{out} is the prevailing mean outdoor air temperature which can be approximated by the exponentially-weighted running mean temperature. In this running mean α is set to 0.8 (the ANSI/ASHRAE Standard 55 suggests using a value between 0.6 and 0.9 [3]), hence the weights give more importance to the mean daily temperatures of recent days:

$$T_{out} = (1 - \alpha) \cdot [T_{e(d-1)} + \alpha \cdot T_{e(d-2)} + \alpha^2 \cdot T_{e(d-3)} + \alpha^3 \cdot T_{e(d-4)} + ...] \tag{3}$$

where $T_{e(d-1)}$ is the mean outdoor temperature of the day before the day in question, and $T_{e(d-2)}$ is the mean outdoor temperature of the day before that, and so on.

The centre point of these bounds, i.e. the comfort temperature (T_{comf}), is given by:

$$T_{comf} = 0.31 \cdot T_{out} + 17.8 \quad (4)$$

The ASHRAE adaptive limits are valid for spaces without any mechanical cooling system installed and with no heating system in operation, for prevailing mean outdoor air temperatures ranging between 10 and 33.5°C.

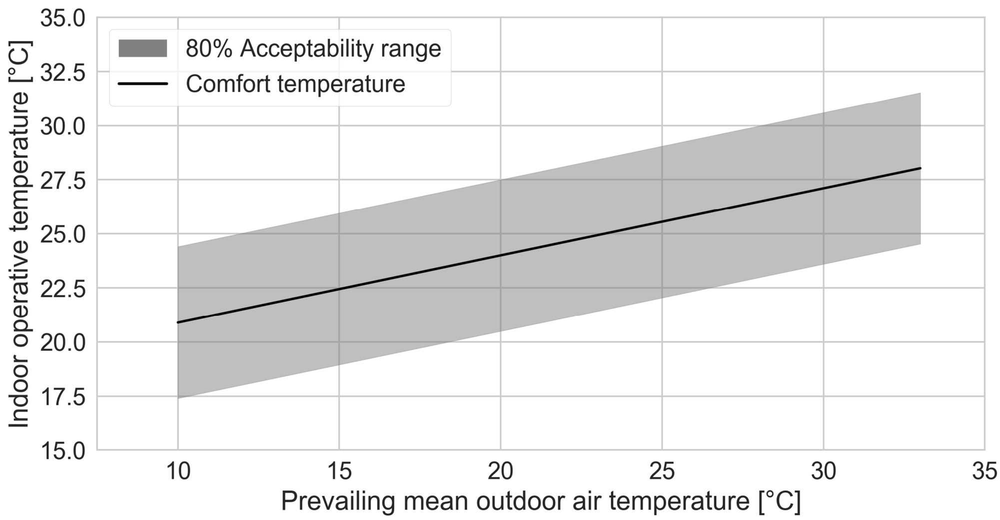


Figure 1: Acceptable operative temperature ranges for naturally conditioned spaces according to the ANSI/ASHRAE Standard 55-2013.

Greater detail of the background and use of the adaptive model can be found in references: [2, 30]. Despite a series of criticisms of this approach, especially regarding its accuracy when compared to Fanger's heat-balance model [34], this remains the most widely used model for designing free-running environments.

1.3. Köppen Climate Classifications

The Köppen Climate Classification System is the most widely used scheme for classifying climates [13]. Its categories are based on the annual and monthly averages of precipitation and temperature. It recognizes five major climatic types, each designated by a capital letter. Figure 2 shows the distribution of these climates.

Tropical Moist Climates (A)

Tropical moist climates extend north and south from the equator to approximately 15 to 25° of latitude. In these climates all months have average temperatures greater than 18°C and annual precipitation greater than 1.5 m.

Dry Climates (B)

In this climate potential evaporation and transpiration exceed precipitation. These climates extend from 20 to 35° north and south of the equator and in large continental regions of the mid-latitudes frequently surrounded by mountains.

Moist Subtropical Mid-Latitude Climates (C)

This climate commonly has warm and humid summers with mild winters. It extends from 30 to 50° of latitude mostly on the eastern and western borders of continents. During the winter, a dominant feature is a mid-latitude cyclone. Convective thunderstorms are common in summer.

Moist Continental Mid-Latitude Climates (D)

Moist continental mid-latitude climates with relatively warm to cool summers and cold winters, and existing pole-ward of the C climates. The average temperature of the coldest month is less than -3°C and the warmest month greater than 10°C. Winters would be considered severe with snowstorms, strong winds, and cold from continental polar or arctic air masses.

Polar Climates (E)

Polar climates are cold year-round and even the warmest month will be less than 10°C. Such climates are found on the northern coast of North America, Europe, Asia, and on the landmasses of Antarctica and Greenland.

The locations selected for the study are: Ceará (Brazil, Köppen A), Riyadh (Saudi Arabia, Köppen B), Sydney (Australia, Köppen C), Helsinki (Finland, Köppen D), and Nuuk (Greenland, Köppen E).

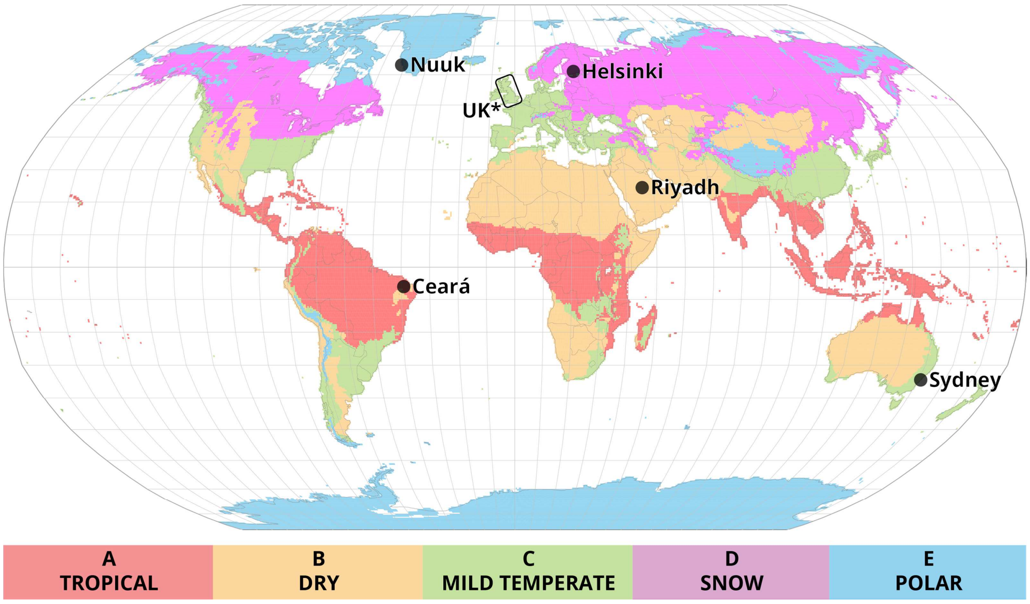


Figure 2: Major Köppen climate classifications; adapted from [13]. UK*: London, Manchester and Edinburgh.

2. Materials

In the following we introduce the historical and synthetic weather files used in this paper.

2.1. Base years

The National Centers for Environmental Information (NCEI), from the National Oceanic and Atmospheric Administration (NOAA), provides public access under request to a large database of global environmental data. This database was used to create the mean daily temperatures of the last thirty years (up to 2015) of five locations (Ceará, Riyadh, Sydney, Helsinki and Nuuk) corresponding to the five Köppen regions (A-E). In the case of Sydney, only 18 years of data were available.

In addition, the British Academic Data Centre (BADC) repository [35] was used to create 22 years of data for London, Manchester, and Edinburgh in the UK (Köppen C), and to build TRY and DSY.

2.2. Synthetic Weather

Given the limitations in the length of the historical weather record in many locations, interest has grown in the use of synthetic weather data produced by weather generators. These programs use the observed long-term statistical weather record at a location to produce an hourly time series of the common weather variables.

Two advantages of weather generators over other data sources are that they can provide a near infinite number of possible years of weather, and they can be run into the future, thereby accounting for climate change. The weather generator used in this work was that used by the UK Climate Impacts Programme [36]. The probabilistic projection methodology in UKCP09 involves sampling climate modelling uncertainties by combining results from perturbed variants of the UK Met Office global climate model (HadCM3) with projections from an ensemble of four alternative international climate models used by the fourth IPCC assessment report [37]. Running the weather generator involves declaring a time period and a world carbon emission scenario. In this work the time slice was set to the 2020s, as this is the closest to the current date, and the emission scenario to low (to create the minimum perturbation from current weather). 3,000 years of weather was generated for London, Edinburgh and Manchester.

2.3. Central England Temperature Record

The Central England Temperature record was originally published by Gordon Manley in 1953 and subsequently extended and updated in 1974 [38], following many decades of work. The mean surface air temperatures, for the Midlands region of England, are given from the year 1659 to the present (daily since 1772). This record represents the longest series of temperature observations in existence.

3. Methods

The methodology is presented in Figure 3 and consists of the following steps:

1. Extract the multi-year daily weather time series for all the study locations (one in each of the five major Köppen climate classifications and three in the UK) and create the representative years for the UK locations (London, Edinburgh and Manchester). Any missing data in the observed time series was replaced with data just prior to the missing section.
2. Use equations (1) to (4) to transform the multi-year and representative temperature time series to comfort indoor temperature time series for all locations around the world. The calculation of the running mean outdoor air temperature requires a

warming up period, which varies depending on how many days are being considered for its calculation. For example, a 30-days running mean cannot be computed for the first 30 days of January using data for a single year. In such situations, the running mean is calculated using data from December of the same year as an approximation.

3. Compute the mean of the daily standard deviations of the temperature time series for each location and compare them in order to judge their variability; repeat for the running mean time series.
4. For London, Edinburgh and Manchester, compare the upper and lower bounds of the comfort temperature given by the reference years to the range given by the complete multi-year set of comfort temperatures in order to discover if days exist that are outside the bounds given by the representative comfort years.
5. Compute the mean of the daily standard deviations for the 3,000 years of synthetic weather generated for London, Edinburgh and Manchester. If this matches that given by the historical weather records, compute return periods for any excursions of the running mean time series. A return period is an estimate of the regularity with which a certain event will occur. So, if a return period is N, it is expected to occur once every N years. In our case the event is the excursion in the running mean time series.
6. Create a new set of *probabilistic* adaptive comfort equations based on these return periods.
7. Validate the return periods by using 358 years of data from the Central England Temperature Record; then the predictions themselves by comparing the excursions predicted by the model and those given by the weather generator for a different time period.

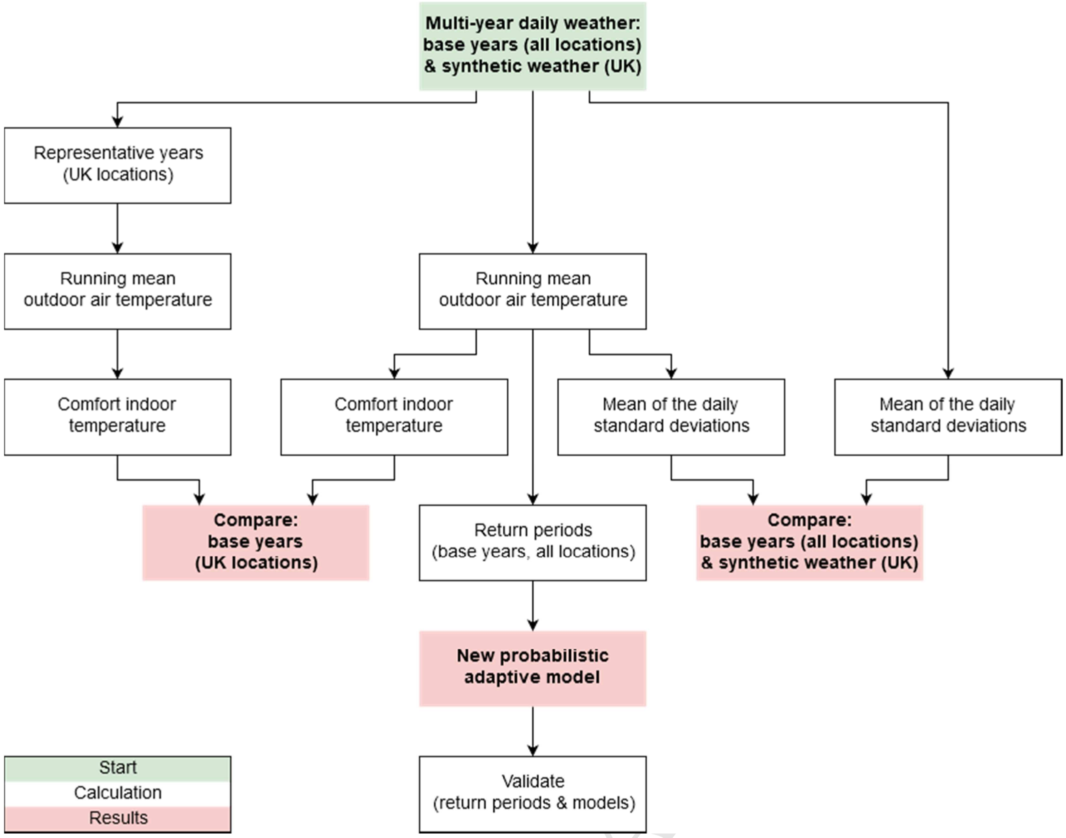


Figure 3: Method workflow. Locations are Ceará, Helsinki, Nuuk, Riyadh, Sydney, Edinburgh*, London* and Manchester*. The UK locations (*) include both historical weather and synthetic weather from the Weather Generator.

4. Calculations and Results

In the following we show the variability of the studied historical weather time series and we introduce and validate a new probabilistic adaptive comfort theory.

4.1. Weather variability

Figure 4 shows the daily mean outdoor temperature record for London over 22 base years, together with two common reference years (TRY and DSY). It is clear that for this Köppen Class C location, there is a large year-on-year variation in the temperature, with some winter days being almost as warm as some summer days. Converting these time series to upper and lower allowable indoor temperature limits using equations (1) to (3) gives Figure 5, from which it is seen that the variability in both the upper and lower bound reaches up to 3.5°C, i.e. almost half the 7°C that the adaptive comfort model gives for the distance between the bounds, and equal to the distance between the comfort temperature, given by equation (4), and the bounds.

Repeating this analysis for the other locations shows similar results (Figure 6), however it is clear that the inter-year range found depends greatly on the location — implying that in some locations the potential error created by using a single representative year will be greater than in others.

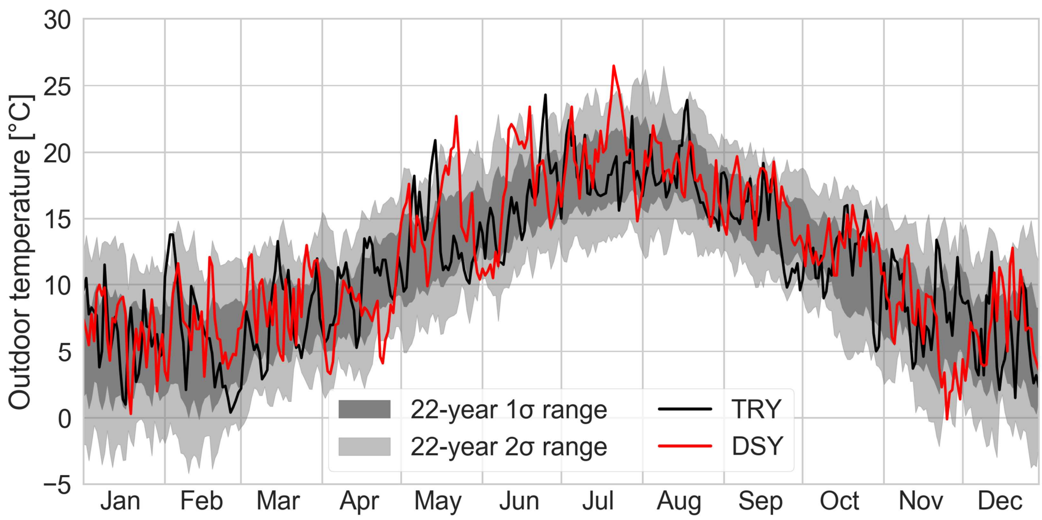


Figure 4: Daily mean outdoor temperatures for London (22 base years). The shaded areas indicate 1 and 2 standard deviations (σ) of the daily mean outdoor temperatures.

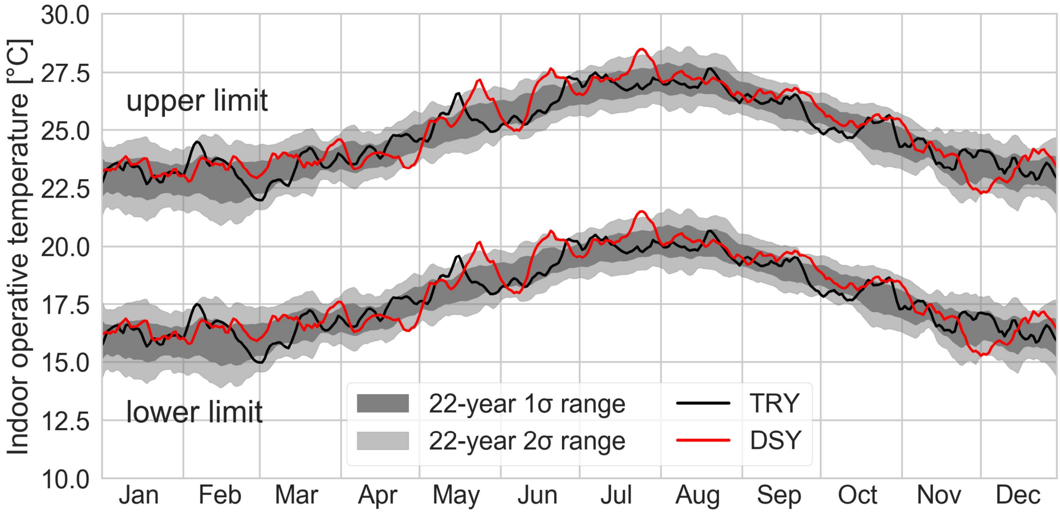
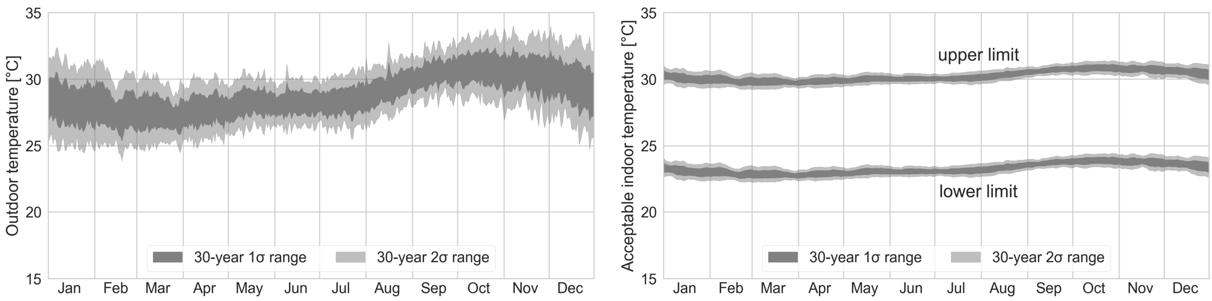
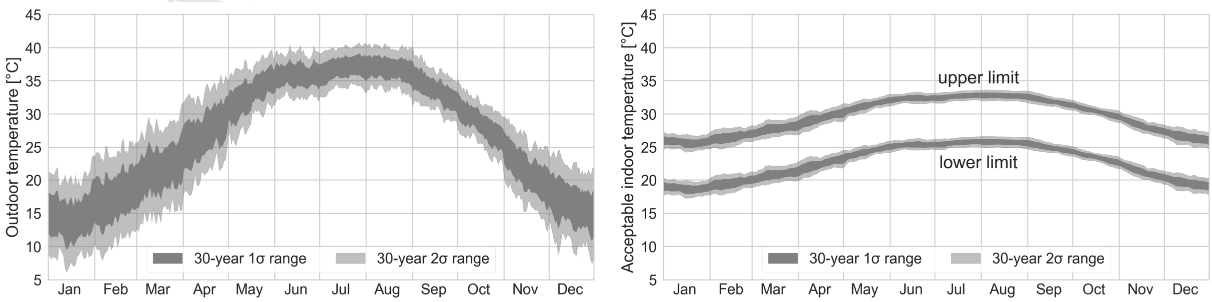


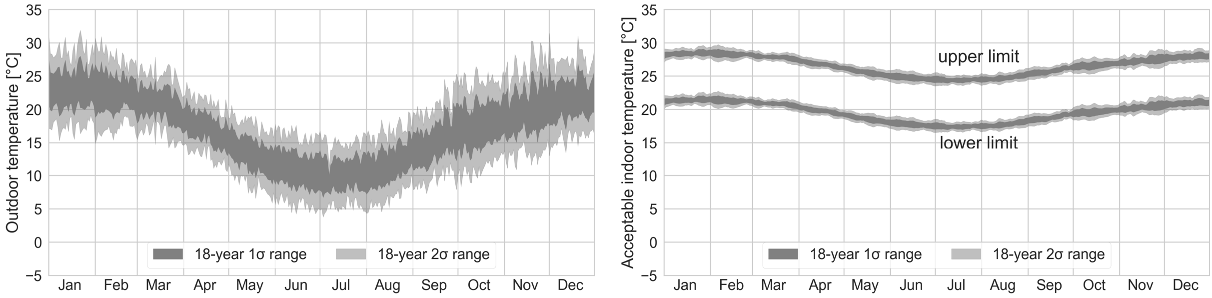
Figure 5: Upper and lower bounds of acceptable indoor temperatures for London (22 base years), derived from equations (1) to (3). The comfort bounds extend outside the 10 to 33.5°C running mean temperature range implied by the adaptive comfort theory. The shaded areas indicate 1 and 2 standard deviations (σ) of the daily acceptable indoor operative temperatures.



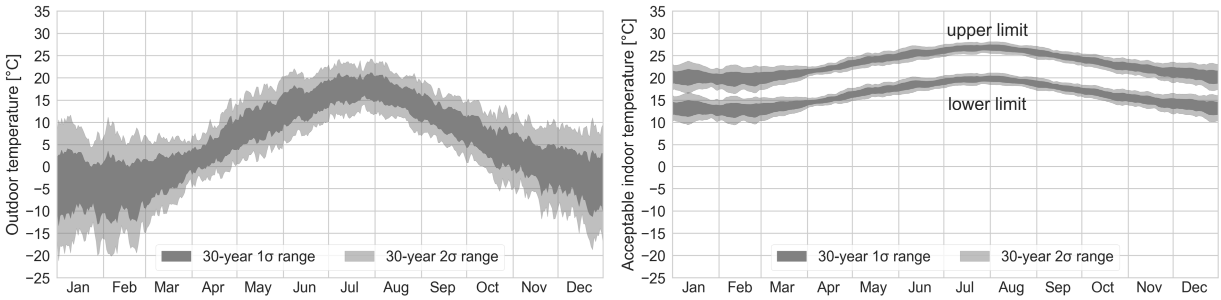
Ceará, Brazil (Köppen A)



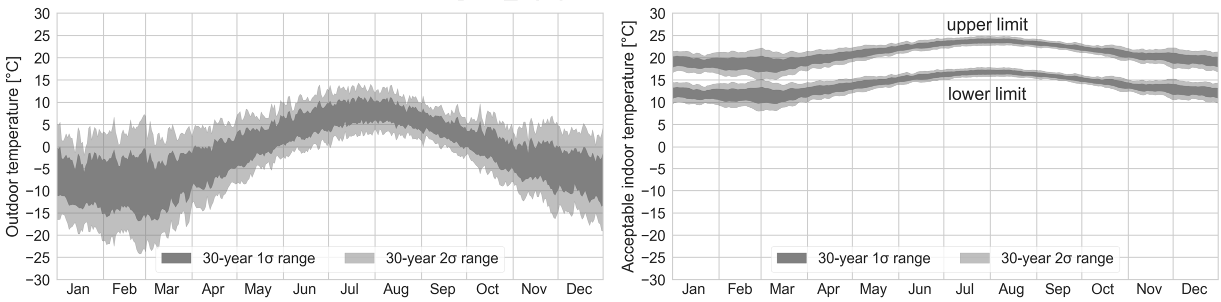
Riyadh, Saudi Arabia (Köppen B)



Sydney, Australia (Köppen C)



Helsinki, Finland (Köppen D)



Nuuk, Greenland (Köppen E)

Figure 6: Daily mean outdoor temperatures (left in each pair) and acceptable indoor temperatures (right in each pair) for the study locations. The comfort bounds extend outside the 10 to 33.5°C running mean temperature range implied by the adaptive comfort theory. The shaded areas indicate 1 and 2 standard deviations (σ) of the daily mean temperatures.

Table 1 shows the spread in the source data and the spread after application of equation (3) for 3 locations in UK (London, Edinburgh and Manchester). This is represented as the mean of the daily standard deviations of the mean temperatures calculated both over all the mean daily temperatures ($\sigma_{day,Tout}$) and only over the restricted 10 to 33.5°C range implied by the adaptive comfort theory ($\sigma_{day,res,Tout}$). $\sigma_{day,Trm}$ and $\sigma_{day,res,Trm}$ are the equivalent quantities calculated using the running mean given by equation (3). The main logic for calculating the restricted standard deviation is that the model is to be used over the 10 to 33.5°C running mean temperature range where it is considered valid. This has also the advantage of being a more robust statistical indicator since the extreme periods, if present, are discarded.

Although it would be possible to calculate return periods for the data shown in Figures 5 and 6, they have the potential to be poor estimates for use as the basis of return periods, as relatively few years of data are available. We therefore need to obtain an estimate of how reliable any these standard deviations are by using a longer time series. The weather generator was therefore used to create 3,000 years of synthetic weather for London, Edinburgh and Manchester in the UK. $\sigma_{day,Tout}$, $\sigma_{day,res,Tout}$, $\sigma_{day,Trm}$ and $\sigma_{day,res,Trm}$ for the 3,000 years of synthetic weather are reported in Table 1.

The data of Table 1 confirms the visual suggestion of Figures 4 and 5, i.e. that the variability in the temperatures is substantial. It also confirms that the standard deviations generated using the base years are good estimates of the true standard deviations, both in terms of the external temperature series T_{out} and running mean temperature T_{rm}.

These results clearly show that under the adaptive comfort theory and a single reference year, it is possible to design buildings which might easily fail in a subsequent year.

Table 1: Variability in the weather data for 3 locations in UK over the 22 base years used to form the reference years, and over the 3,000 synthetic weather years.

	Base years (22 years)				Synthetic weather (3,000 years)			
	$\sigma_{day,Tout}$	$\sigma_{day,res,Tout}$	$\sigma_{day,Trm}$	$\sigma_{day,res,Trm}$	$\sigma_{day,Tout}$	$\sigma_{day,res,Tout}$	$\sigma_{day,Trm}$	$\sigma_{day,res,Trm}$
London	2.88	2.58	1.94	1.77	2.95	2.69	1.99	1.76
Edinburgh	2.91	2.64	2.07	1.94	2.63	2.29	1.74	1.46
Manchester	2.84	2.58	2.30	2.45	2.79	2.53	1.85	1.60

Extracting the standard deviations for the other study locations gives Table 2. Again, the spread is considerable. It is also to be noticed that for locations of Köppen E climate (such as Nuuk in Greenland) there is no spread available for $\sigma_{day,res,Tout}$ and $\sigma_{day,res,Trm}$ as the running mean outdoor temperatures are always outside the range of applicability (10 to 33.5°C) of the adaptive model.

Table 2: Variability in the worldwide weather data.

	Base years (n years)				
	n	$\sigma_{day,Tout}$	$\sigma_{day,res,Tout}$	$\sigma_{day,Trm}$	$\sigma_{day,res,Trm}$
Ceará (Brazil, Köppen A)	30	1.17	1.17	0.79	0.79
Riyadh (Saudi Arabia, Köppen B)	30	2.39	2.78	1.60	1.77
Sydney (Australia, Köppen C)	18	2.67	2.69	1.36	1.37
Helsinki (Finland, Köppen D)	30	3.96	2.97	2.88	2.17
Nuuk (Greenland, Köppen E)	30	3.83	n.a.	2.68	n.a.

4.2.A new probabilistic adaptive comfort equation

The probability for a normally distributed random variable Z with expected value 0 and variance 1 of having a value smaller than z, i.e. $p(Z \leq z)$, is given by the cumulative distribution function $\tau(z)$. To straightforwardly use τ with no need to look up the inverse of the normal distribution we can use the simple approximation based on [39]:

$$z \cong \frac{(p)^{0.135} - (1-p)^{0.135}}{0.1975} \tag{5}$$

This approximation is valid for the case in which $p \geq 0.5$. Considering a return period N, we find that $p = 1 - \frac{1}{N}$ (i.e. p can be interpreted as the probability of not obtaining a value that is smaller or equal to a one-in-N-year extreme event) and therefore equation (5) becomes equation (6), which correctly covers all the return periods longer than 2 years.

$$z \cong \frac{\left(1-\frac{1}{N}\right)^{0.135} - \left(\frac{1}{N}\right)^{0.135}}{0.1975} \tag{6}$$

Given a reliable estimate of $\sigma_{\mathrm{day,res,Trm}}$ we can then calculate the excursion for any return period as $z(N) \cdot \sigma_{\mathrm{day,res,Trm}}(\mathrm{K})$. This excursion is the ΔT required to adjust the model to make a building resilient to a one-in-N-year extreme event in a given location (K). Table 3 shows examples for these excursions. In addition, we can create a new probabilistic thermal comfort model based on the following equations:

$$T_{\mathrm{upper,N}} = (0.31 \cdot \mathrm{Tout} + 17.8) + 3.5 - \mathrm{z(N)} \cdot \sigma(K), \quad \text{and} \tag{7}$$

$$T_{\mathrm{lower,N}} = (0.31 \cdot \mathrm{Tout} + 17.8) - 3.5 + \mathrm{z(N)} \cdot \sigma(K) \tag{8}$$

where, as before, T_{out} is given by equation (4), σ depends on the climate K where the building is located and z depends on the selected return period N. Ideally K would be fully localized, however, as these are standard deviations, not means, the values given in Table 3 can be used as approximations over all locations of identical Köppen classification.

Table 3: Excursions for a range of return periods for the locations studied (i.e. values for $\Delta\mathrm{T} = \mathrm{z(N)} \cdot \sigma(K)$ in equations (7) and (8)).

	Excursion ΔT (°C)			
Return period N (years)	5	10	25	100
Ceará (Brazil, Köppen A)	0.66	1.01	1.39	1.85
Riyadh (Saudi Arabia, Köppen B)	1.48	2.27	3.11	4.14
Sydney (Australia, Köppen C)	1.15	1.76	2.41	3.20
Helsinki (Finland, Köppen D)	1.82	2.78	3.81	5.07
Nuuk (Greenland, Köppen E)	n.a.	n.a.	n.a.	n.a.
London, (UK, Köppen C)	1.48	2.27	3.11	4.14

Plotting equations (7) and (8) we have a probabilistic chart similar to that of Figure 1, but this time with upper and lower limits defined by a series of the probabilistic lines, in this case shown for N = 5 (Figure 7).

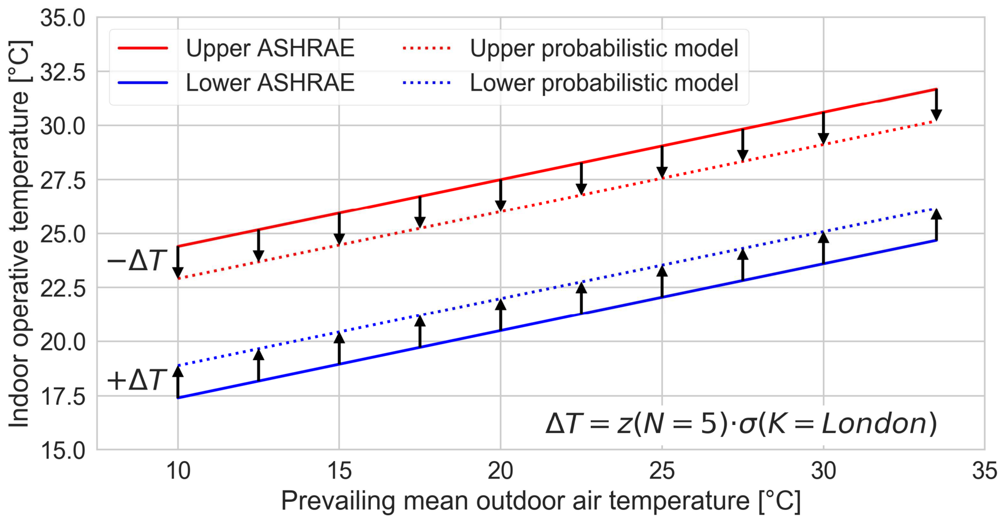


Figure 7: Probabilistic adaptive thermal comfort limits for London, from equations (7) and (8). The location of the return period lines is climate dependent.

4.3. Validation

Validation requires two steps: (1) looking at the return periods, (2) looking at the excursions above the comfort line for a building. The return period estimates are based on the standard deviations, and although in the above we have shown that σ from the weather generator is similar to σ from the 22 base years, this does not show that is correct, particularly over the number of standard deviations needed for large return periods.

The Central England Temperature Record spans 358 years, from 1659 to today (daily since 1772). A Shapiro-Wilk normality test [40] based on the annualised mean daily temperature[1] within the record gives W = 0.995 and p-value = 0.237, thereby providing no evidence to reject the normality of the data (as p-value >> 0.05). For this data, the values shown in Table 4 are obtained; these are very similar to those from the 22 base years for London and the

[1] Normality tests are unsuitable for large datasets and 358 years of daily temperatures represent more than 130,000 values. To apply the normality test they have been reduced to 358 values by computing annual means.

weather generator. So the standard deviations reported earlier would seem to be reasonable, validating the return periods.

Table 4: Variability in the Central England Temperature Record.

	$\sigma_{day,Tout}$	$\sigma_{day,res,Tout}$	$\sigma_{day,Trm}$	$\sigma_{day,res,Trm}$
Central England Temperature Record (358 years)	2.77	2.33	1.88	1.57

To validate the predicted excursions, and demonstrate the method, the number of hours that a building subjected to a one-in-N-year weather breaches the upper comfort equation in the ASHRAE model (1) is compared to the number of hours a building subjected to a reference year breaches the one-in-N-year probabilistic upper comfort equation (5). Figure 8 shows this for London with N=100 and σ=1.76 (WG simulations: 100th percentile (1-in-100 risk) and 50th percentile (average case, 50-in-100 risk). The data again came from the weather generator, but this time with a high carbon emission scenario and for the 2080s, thereby ensuring temperatures above the upper threshold. The one-in-100-year has 3,529 hours above the normal comfort line; the reference year has a similar 4,117 hours above the one-in-100-year probabilistic comfort line, validating the method.

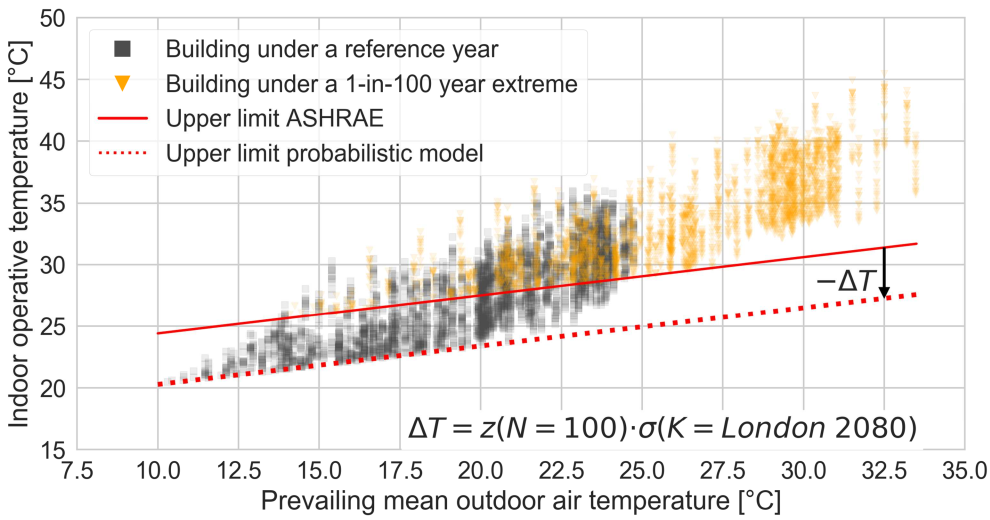


Figure 8: Validation of the method by the comparison of the excursions given by a one-in-100-year year above the normal comfort upper limit line, and the excursions of the reference year above the one-in-100-year probabilistic comfort line. Each dot represents one hour of weather data from either weather files.

5. Discussion

With our new method we can define how sensitive the building or occupants are to a warmer or cooler than average year. For example, an office might be considered robust, with the potential to send occupants home, so a designer might chose to design to be resilient to a one-in-five year, so N=5. Whereas a care home might chose to be far more cautious and desire to be resilient to a one-in-one-hundred-year event, giving N=100. This number is used to define the probabilistic upper or lower line of Figure 7, together with the standard deviation found by using the weather data available at the location in question, as in Table 1 and 2. The results from any design simulation are then compared to this line, and the design altered so that all hours, or not more than a pre-specified number of hours, are above or below the probabilistic line. Considering the case in which our design is specifically addressing an overheating issue, the upper limit should be used. In case of undercooling, the lower limit is to be considered instead.

Our analysis shows that the year-on-year weather variability depends greatly on the location. This implies that in some locations the potential error created by using a single representative year will be greater than in others. Our new probabilistic method is able to take into account this weather variability and promote a resilient building design in any location.

One advantage of this new probabilistic method over the use of multiple probabilistic years for design is that, by retaining the single reference year, all simulations reported to the client, regulatory bodies and other members of the design team are consistent, and based on a single weather file well known to all; whereas, if different weather files are used to represent different return periods, then it is difficult to obtain temporarily consistent simulation results. Another advantage is that it requires only one run of the simulation engine.

6. Conclusions

This paper asks if the natural variability in weather is of such a scale that the academic and practicing engineering community should switch from using a single representative year when applying an adaptive thermal comfort theoretic approach, as is commonly used with naturally ventilated buildings, to a probabilistic one.

For one location in each of the five major Köppen climate classifications and three locations in the UK, observed historical weather files were collated and used to create multi-year adaptive thermal comfort temperature time series. Despite these containing (by definition) a smoothing of the weather data, these new time series showed great variability, demonstrating years when the upper bound in winter was higher than in summer. Then, by using a state-of-the-art validated weather generator, 3,000 years of synthetic weather data was created for the three locations in the UK and the variability in these was shown to match that of the base years used to form common reference years. From this, return periods were found for excursions of the running mean temperatures. This then allowed a new *probabilistic* comfort model to be developed.

In this new probabilistic adaptive comfort theoretic approach, a building is seen to fail not when its internal conditions lie outside the fixed comfort bounds when simulated with a representative year, but when it exceeds the N-year comfort bounds, with N being set by regulation, or dictated by the situation. For example, a hospital or care home might be expected to not breach the bounds more than once in fifty or more years; whereas it might be reasonable to allow a retail complex to be designed against a one-in-five-year limit.

Given the deaths of 14,000 people in Paris in the 2003 heat wave, mainly in naturally ventilated buildings, the additional resilience that the adoption of this approach would give is highly important. Further pertinence is provided by concerns over likely increases in mortality and morbidity in buildings due to a rapidly warming climate.

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